

MODELING THE SURFACE ROUGHNESS DURING MILLING IN OFF - LINE MONITORING

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ABSTRACT

Off-line process control improves process efficiency. This paper examines the influence of three cutting parameters on the surface roughness in face milling as part of the off-line process control. The experiments were carried out in order to define model for process planning. Cutting speed, the feed per tooth and the depth of cut were taken as influential factors. Two modeling methodologies, namely regression analysis and neural networks have been applied to experimentally determined data. Results obtained by the models have been compared. Both models have the relative prediction error below 10%. The research has shown that when training dataset is small neural networks modeling methodologies are comparable with regression analysis methodology and furthermore it can even offer better result, in this case average relative error of 6,64%. Advantages of off-line process control which utilizes process models by using this two modeling methodologies were explained in theory.

Keywords: Off-line process control; Surface roughness; Regression Analysis; Radial basis function neural network

1. INTRODUCTION

Process control is the manipulation of process variables motivated by process regulation and process optimization. The adaptation of process variables therefore has the purpose of reduction production cost or cycle time. Usually it is done through adjusting three impact factors: the cutting speed, the feed and the depth of cut and employing parameter estimation to adapt the model to changing process conditions. Process control can be performed as an on-line or off-line process. Off-line process control refers to preliminary defining process variables as a part of process planning stage. Selection of variables is usually based on a machine book or the operator's experience therefore computer aided process planning is a step forward and provides better results in production. Complex manufacturing and technological processes nowadays claim implementation of control systems using sophisticated mathematical and other methods for the purpose of their efficient control. Thus a research is needed to get the mathematical approximations of machining processes and appearing phenomena as better as possible. Engineers face in manufacturing two main practical problems. The first is to determine the values of the process parameters that will allow achieving expected product quality and the second is to optimize manufacturing system performance with available resources. The decisions made by manufacturing engineers are based not only on their experience and expertise but also on understanding the machining principles and mathematical relations among influential parameters. Machining process is determined by the mutual relationship of the input values and its efficiency can be measured through output values. The great number of input values, as well as a fact that they have quantitative and qualitative nature contributes to the large expands of possible interactions and their complexity.

The aim of this research is to find mathematical models which relate the surface roughness with three cutting parameters, the cutting speed (v_c), the feed per tooth (f_i) and the depth of cut (a_p), in face milling. In this research two different approaches have been used in order to get the mathematical models. The first approach is a design of experiment (DOE) together with an analysis of variance

(ANOVA) and regression analysis (RA), and the second one is modeling by means of artificial neural networks (ANNs). In the past, the DOE approach has been used to quantify the impact of various machining parameters on various output parameters, but nowadays proved ANNs as method with great ability for mapping very complex and nonlinear systems. Milling process is an example of such a system and that justifies the usage of ANNs.

2. EXPERIMENTAL SETTINGS

The type of machine used for the milling test was machining center VC 560 manufactured by Spinner. Test sample used in experiment were made of steel 42CrMo4 with dimensions 110x220x100 mm. The face milling experiments were executed by a tool CoroMill 390 with three TiN coated inserts, produced by Sandvik. Average surface roughness R_a of machined workpieces was periodically measured by a Surftest SJ-301, produced by Mitutoyo. The measurements of surface roughness were taken on predestinated five different places on the sample. During the process of measuring, the cutoff length was taken 0,8 mm and the sampling length 5,6 mm. All experiments were carried out without cooling and lubrication agents. Cutting parameters as the cutting speed, the feed per tooth and the depth of cut were taken within their region of interest of 120 to 140 m/min, 0.10 to 0.20 mm/tooth and 1.0 to 1.5 mm, respectively. Altogether 33 experiments were conducted. Twenty experiments were conducted in order to allow performing ANOVA and regression analysis, and additional 13 experiments to obtain additional data for performing RBF modeling and verification of both models. For those experiments, the values of the cutting parameters were randomly chosen within the range. Altogether, 28 data pairs have been chosen for the procedure of training and testing RBF model. In this work, the design of experiment was achieved by the rotatable central composite design (RCCD). Five experiments were discarded because RCCD demands the six repetitions at the center point. Before the training and testing, all input and output data have been scaled within the interval -0.9 and 0.9. After the training, models were tested to their generalization ability. Testing was performed with the data that had not been used in training process. In order to conduct the training and testing of the neural network models, a neural network toolbox embedded in MATLAB was used. Eight data pairs, randomly selected, were utilized for the validation of both regression analysis and ANN modeling.

3. ANALYSIS OF RESULTS OF BOTH RA AND NEURAL NETWORKS SIMULATION

Measured values of surface roughness obtained by 20 experiments are presented in Table 1. The ANOVA and RA have been performed using program package "Design Expert 6".

Table 1. Experimental data

Exp. number	v_c (m/min)	f_t (mm/tooth)	a_p (mm)	R_a (μm)	Exp. number	v_c (m/min)	f_t (mm/tooth)	a_p (mm)	R_a (μm)
1	120,00	0,10	1,00	0,59	11	130,00	0,07	1,25	0,48
2	140,00	0,10	1,00	0,53	12	130,00	0,23	1,25	1,82
3	120,00	0,20	1,00	1,45	13	130,00	0,15	0,83	0,85
4	140,00	0,20	1,00	1,18	14	130,00	0,15	1,67	0,92
5	120,00	0,10	1,50	0,61	15	130,00	0,15	1,25	0,84
6	140,00	0,10	1,50	0,70	16	130,00	0,15	1,25	0,79
7	120,00	0,20	1,50	1,55	17	130,00	0,15	1,25	0,85
8	140,00	0,20	0,59	1,19	18	130,00	0,15	1,25	0,81
9	113,18	0,15	1,25	0,73	19	130,00	0,15	1,25	0,86
10	146,82	0,15	1,25	0,50	20	130,00	0,15	1,25	0,87

By applying the regression analysis the coefficients of regression, multi-regression factors, standard false evaluation and the value of t -test have been assessed. After omitting insignificant factors the mathematical model for surface roughness R_a is obtained as follows:

$$Ra = -10,584 + 0,17114 \cdot v_c + 14,25341 \cdot f_i - 6,0408 \cdot 10^{-4} \cdot v_c^2 + 52,3455 \cdot f_i^2 - 0,1645 \cdot v_c \cdot f_i \quad (1)$$

The square of regression coefficient (r^2) is 0.9829.

Results of training and testing, in the form of regression analysis are shown in Figure 1. R is a measure of agreement between the outputs and targets, and the aim is to get R-value close or equal to 1. In example on Figure 1, it is close to 1 and that indicates good fit.

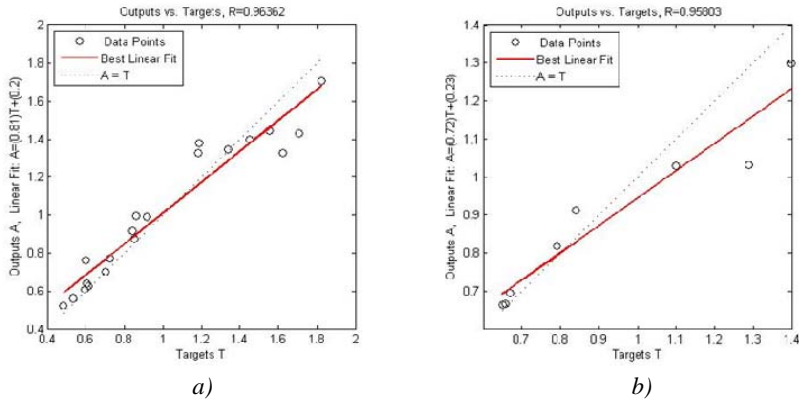


Figure 1. Results of training (a) and testing for generalization ability (b)

Table 2 shows 13 additional measured experimental data. Data marked with asterisk (*) were not used either in the network training or in the regression analysis. These data were utilized for the validation of both regression analysis and ANN modeling.

Table 2. Additional measured experimental data

Exp. number	v_c (m/min)	f_i (mm/tooth)	a_p (mm)	Ra (μm)	Exp. number	v_c (m/min)	f_i (mm/tooth)	a_p (mm)	Ra (μm)
21*	135	0,13	1,2	0,79	28*	121	0,12	1,2	0,64
22	132	0,16	1,1	0,86	29	139	0,19	1,1	1,61
23*	131	0,14	1,4	0,82	30*	138	0,15	1,3	1,46
24	137	0,19	1,4	1,71	31*	135	0,1	1,5	0,71
25	125	0,11	1,3	0,60	32*	120	0,12	1,2	0,65
26	123	0,18	1,5	1,34	33*	127	0,18	1,4	1,60
27*	129	0,17	1,1	1,55					

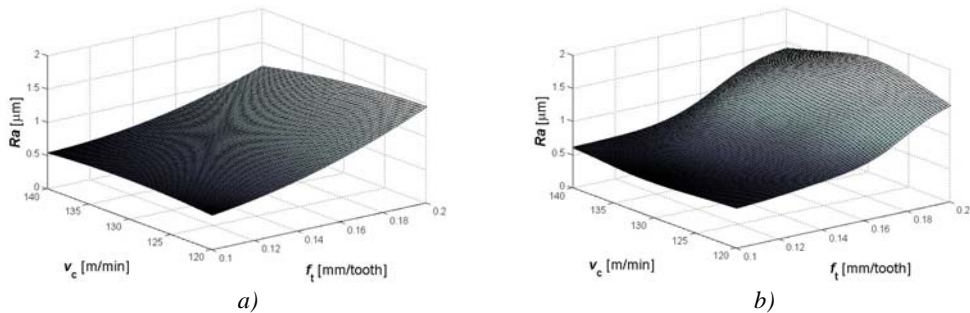


Figure 2. Response surface for surface roughness as a function of cutting speed and feed rate obtained from RBF (a) and RA (b); for constant depth of cut of 1,25 mm

Figure 2 shows the results obtained from RA and RBF for the surface roughness and its dependence on cutting speed and feed per tooth. Observing the changes of Ra with increasing of cutting speed, the connection between two phenomena is established. Therefore, cutting speed is closely related to emergence of build-up edge (BUE) and that implies its effect on machined surface roughness. Increasing the cutting speed the influence of BUE is reduced, and also increases surface quality, but exaggeration in the increase of cutting speed does not influence the further reduction of surface roughness because tool wear is simultaneously increased and it keeps roughness nearly constant. Feed per tooth is directly proportional to surface roughness with the power of two.

In order to test which modeling method gives better prediction, a relative error of deviations from measured values have been calculated. Validation of both models was performed with the testing data set that had not been used in training process. Relative errors obtained using RA and RBF methodologies have been compared. The results indicate that RBF model offers the best prediction capability with average relative error of 6,64%.

4. CONCLUSION

The purpose of this study is the research of possibility of the surface roughness modeling to collect the information needed for effective machining planning as part of off-line process control. The influence of the cutting speed, the feed per tooth and the depth of cut on surface roughness in face milling process have been examined in the study, and in order to model dependency between those parameters regression analysis and neural network methodology were used. Regarding the results, both methodologies are found to be capable for accurate predictions, although neural network models gives somewhat better predictions, with approximately relative error of 6,64%. The research has shown that when training data set is relatively small (as in the study) neural network models is comparable with RA methodology and furthermore it can offer even better results. More accurate predictions ultimately improve off-line process control resulting in significant reduce of machining cost. Nevertheless, despite years of research and the multitude of success stories in the laboratory, only a small amount of modern technologies has been transferred to production. Therefore off-line process control, as an approach that demonstrates its capabilities to be applied in practice and easily integrated in existing conditions still represents a key for successful machining and also the bridge between machining research and the production line.

5. REFERENCES

- [1] Furness, R. J., Ulsoy, A. G., and Wu, C. L., *Feed, speed, and torque controllers for drilling*, ASME Journal for Manufacturing Scientists and Engineers, 1996, 118, 2–9.
- [2] Landers, R.G., Usloy, A.G., Furness, R.J., *Process monitoring and control of machining operations*, Mechanical Systems Design Handbook, CRC Press, Chapter 6, 2002, pp. 85-119.
- [3] Lu, C., *Study on prediction of surface quality in machining proces*, Journal of materials processing technology 205 (2008), pp. 439–450
- [4] Bajić, D., Belaić, A., *Mathematical modeling of surface roughness in milling process*, In: Proceedings of the 1st International Scientific Conference on Production Engineering (ISC), Lumbarda, Croatia, June/July 2006, pp. 109-115,
- [5] Oktem, H., Erzurumlu, T., Kurtaran, H., *Application of response surface methodology in optimization of cutting conditions for surface roughness*, Journal of Material Processing and Technology 170, 2005, pp. 11 – 16.
- [6] Benardos, P.,G., Vosniakos, G.,C., *Prediction of surface roughness in CNC face milling using neural networks and Taguchi's design of experiments*, Robotics and Computer Integrated Manufacturing 18 (2002) 343–354
- [7] Tugrul, O., Yigit, K., *Predictive modeling of surface roughness and tool wear in hard turning using regression and neural networks*, International Journal of Machine Tools & Manufacture, 2005, 467-479.
- [8] Benardos, P.,G., Vosniakos, G.,C., *Prediction surface roughness in machining: a review*, Journal of Machine Tools & Manufacture, 2002, 833-844.
- [9] Montgomery, D.C., *Design and analysis of experiments*, New York: John Willy & Sons, Inc., 1997,
- [10] MATLAB User's Guide: The Mathworks, 2003, Neural Network Toolbox.